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Improved ANS Lightning Predictors Using
Additional Surface Wind and Electric Field Data

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13. ABSTRACT (Maximum 200 words) Because of the destruction by lightning of Atlas-Centaur 67 and its communication satellite payload on 27 March 1987, new launch commit criteria with respect to lightning were imposed by NASA and the Air Force for missile launches from the national ranges. These criteria are very conservative and restrict the available launch windows, especially during summer months at Kennedy Space Center (KSC) and Cape Canaveral Air Force Station (CCAFS) in Florida. In an effort to expand the launch windows while maintaining safety, we show that neural networks can be trained to generate spatio-temporal maps of predicted probabilities of lightning over the CCAFS/KSC complex.

Input data used for training and testing the neural networks include the five minute averages from all 53 wind sensors, the Total Area Divergence product calculated by Watson, the occurrence of lightning strikes as recorded by magnetic direction finders, and most recently, the electric field mill data. Training the neural network lightning predictor with wind data spanning two days of data and the divergence product increased the PoD to 0.65. The predictor's best performance is at 30–60 minutes in the future. We expect the electric field data to affect near term prediction more than later times.

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Executive Summary

The Air Force's Air Weather Service (AWS) provides weather support, including the forecasting of lightning, to both NASA and the Department of Defense at Cape Canaveral Air Force Station (CCAFS) and at Kennedy Space Center (KSC). Because of the destruction by lightning of Atlas-Centaur 67 and its communication satellite payload on 27 March 1987 (Christian et al., 1988), new launch commit criteria with respect to lightning were imposed by NASA and the Air Force for missile launches from the national ranges. These criteria are very conservative and restrict the available launch windows, especially during summer months at KSC and CCAFS in Florida. This report describes an effort to improve the forecasting of lightning by applying neural networks to the prediction of lightning. Specifically, it is intended to construct and train neural net architectures to generate spatio-temporal maps of predicted probabilities of lightning over the CCAFS/KSC complex. The goal of this work is to improve the precision and accuracy of lightning prediction so that the launch commit criteria may be relaxed while maintaining acceptable safety margins.

A thunderstorm's progress over KSC affects local weather parameters: precipitation, cloud cover, winds and electric fields. Watson et al. 1987 developed correlations between present surface wind convergence events and lightning strikes over the next few hours. Using artificial neural systems (ANS) to process surface winds, Frankel et al. 1989b built the first automatically trainable lightning predictor. Its performance was comparable to that reported by Watson et al. 1987 using wind convergence.

Several approaches are considered in this report for improving the ANS lightning predictor. All should offer significant improvements in performance, but not all could be implemented in this contract effort.

(1) **Additional Lightning Days** for more representative training

> Additional days of wind and lightning data were used to extend the single training day employed in Frankel et al. 1989b.

(2) 'Conditioning' Input Nodes for synoptic weather conditions

'Context' input nodes can be used for introducing the synoptic weather regime discussed by Lopez et al. 1987 in connection with lightning activity over central Florida.

(3) Additional Lightning Prior Times for temporal trends

Frankel et al. 1989b used wind data at a single time, t_0, in the ANS predictor to forecast strikes at t_0, $t_{+1/2}$, t_{+1} and t_{+2}, where the subscript indicates the time of prediction in hours. On the other hand, Lapedes & Farber 1987 used several consecutive values of a time series as inputs to an ANS for generalized, non-linear predictions and for providing a 'mapping' of the underlying systematic behavior of a system. The use of a time series of inputs (e.g. t_0, $t_{-1/2}$, t_{-1}, t_{-2}, &c.) of wind data should be considered.

(4) Addition of E-Fields adds an independent predictive variable

Lightning strikes at distances of up to 50 km induce changes in the local electric field, Anon 1989b. Electric field data combined with wind data in the ANS lightning predictor might improve prediction performance, especially for nowcasting and predictions up to 1 hour.

(5) Addition of Met Data Products to reduce ANS complexity.

Raw wind data (two perpendicular wind speed components) from irregularly spaced wind towers were used by Frankel et al. 1989b. Holle et al. 1988 have shown that wind divergence is of value for lightning prediction. Inclusion of their product among the network inputs is expected to improve the ANS predictor's performance.

This report describes three extensions to our previous work: (1) use of additional lightning day data for network training, (2) use of wind divergence values as an additional input for KSC, and (3) use of time averaged electric field mill data. Improved ANS predictor performance, measured by both higher probabilities of detection (PoD) and low false alarm rates, was achieved.

Prediction results attained are, for most test days, superior to the PoDs of the previous state-of-the-art reported by both Watson et

al. 1987 and Frankel et al. 1989b. This improvement is summarized in the figure below.
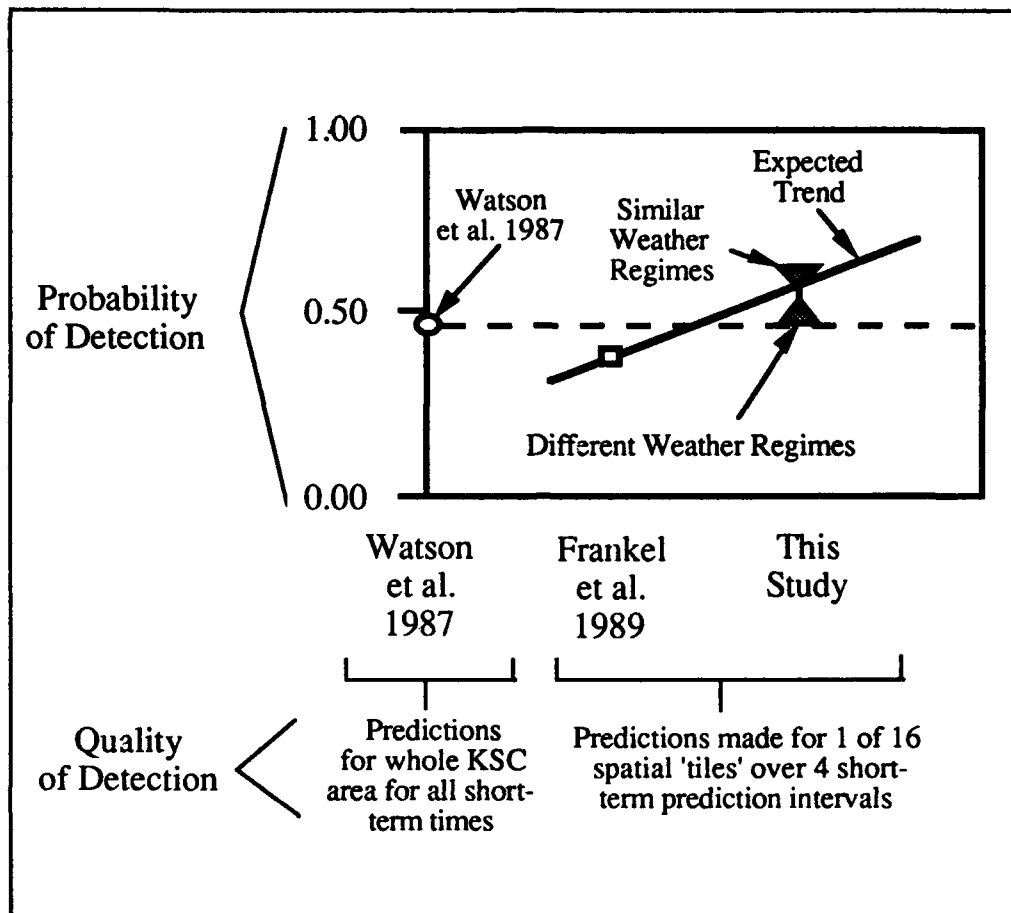
The importance of the synoptic weather regime was investigated by Lopez et al. 1987 who showed correlations between weather regimes and subsequent lightning strike patterns in central Florida. This relation should be tested in future research. Once the synoptic weather is quantified, ANS predictors can be modified to accommodate this 'contextual' information.

The study shows the value of including additional days in the training sets. There are two implications for ANS predictors in operational use. First, further improvements will accrue from the use of larger data sets extending to at least two or three seasons of archived KSC data. Second, once in operation (on site) an ANS lightning predictor's performance will continue to improve, by incremental learning of current data, as a by-product of routine, continuous data collection. Automation of wind, electric field and lightning strike data collection will speed and reduce the costs of these improvements. This will be a great help to AWS meteorologists who

initially have limited acquaintance with local weather conditions due to their rotating tours of duty, Pickle 1990.

Preface

The authors wish to acknowledge contributions to this work by a number of colleagues. First, Dr. Arnold A. Barnes, Jr./LYA, of the Geophysics Laboratory, has provided thoughtful and enthusiastic guidance, expertise, and support through all phases of the project.

Valuable discussions of the data and their interpretation were held at Kennedy Space Center with NASA, Air Force and contractor personnel, including Bill Boyd, Launa Maier, Jim Nicholson, Jan Zysko, Ron Wojtasinski, Bill Jafferis, Hal Herring, Col. John Madura, Dr. Ralph Markson, Mickey Olivier, and John Weems.

Similarly, thorough discussion of the Total Area Divergence product, and the calculated product itself were provided to us by Ronald L. Holle and Irv Watson, respectively, both of NOAA's Severe Storms Laboratory, Boulder, CO.

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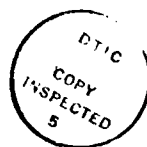
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1. Technical Approach

A method is developed for the prediction of lightning strikes which uses additional days of data and combines electrical and wind inputs. This work continues that on the 'wind field to lightning strike' artificial neural system (ANS) predictor of Frankel et al. 1989b.

The combination of knowledge of the physics of storms and available measurements are the basis for a discussion of prediction techniques in Section 2, "Lightning Prediction Parameters." How weather data can be combined in an improved ANS predictor is described in Section 3, "Data Fusion and Time Series Prediction in Weather Networks." Results from this study are given in Section 4, "Modified ANS Networks." Recommendations on ANS layouts, training and testing procedures and the inclusion of new weather parameters are made in Section 5, "Recommendations."

1.1. Formulating a Prediction Method

Prediction is based on one or a combination of several techniques. When the phenomenon is well modelled excellent predictions can be made that degrade into the future as small initial inaccuracies come to dominate the process. In the present case, given that lightning is not well modeled, four predictive approaches can be used singly or in combination:

1) <u>Guesses</u> of future lightning strikes ('rolling dice');
2) <u>Historical averages</u> of probabilities used for future lightning strikes (the typical approach in the past);
3) <u>Projections of storm motion</u> (used in some current systems, Anon 1989a and Anon 1990); and
4) <u>Time series predictors</u> using current meteorological data.

The technique used here is a time series predictor, 4, using ANS techniques. This approach requires meteorologically relevant measured parameters from which to form independent data sets for training the ANS predictors and testing the resulting predictor. By analogy to multiple regression techniques, inputs may be thought of as predictor variables and outputs play the role of dependent variables. The ANS predictor combines raw predictor variables or products (e. g. Total Area Divergence) to make predictions. The ideal ANS predictor will 'map' the predictor variables into valid predictions. In practice, measurement and environmental noise and limited training sets will degrade the prediction. The challenge in this project

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is the attainment of improved prediction performance in the presence of these deleterious effects.

Besides selecting the physical parameters having high predictive value, one must decide how to configure a neural network to make the best use of these parameters. These issues are how to include variables taken over differing spatial and temporal sampling rates, how to include 'contextual' variables which remain constant during a day, and how to preprocess this mass of data. Overall, this data integration process or 'fusion' is best done when the physical situation is well understood. But ANS are most advantageous precisely when the physics of prediction is not well understood. In any case, inclusion of all relevant weather data is beyond the scope of this study, but the one dimensional parameters most useful to human forecasters can be included. This includes winds, electric fields, and Total Area Divergence, a product derived from wind data.

1.2. Building on the ANS Predictor

There are clearly several ways in which the ANS work of Frankel et al. 1989b could be extended and improved. These include: (a) network training using more than one day's worth of data, (b) inclusion of products, such as the divergence, (c) inclusion of electric field data (d) 'conditioning' input nodes to account for Time of Day and other contextual effects, and (e) the use of input data from times earlier than t_0 to capture the time derivative.

(a) Training with more days of data exposes the neural network to different weather conditions. This enhances a key property of data used to train neural networks: the degree to which the data are representative of the weather situations which will be encountered in practice. A neural network trained on many days will be forced to generalize. It will embody less of what is particular about the weather on any given day and more about what is useful in general for prediction.

(b) Products are the results of processing data with conventional algorithms to arrive at a result which is more useful to forecasters than the raw data. We would expect a neural network's performance to improve if a useful product were included among its inputs, since then the network would not have to build the product on its own. The Total Area Divergence calculated by Watson et al. is such a product; products of radar and satellite imagery are also used by forecasters at Kennedy Space Center (KSC).

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(c) Inclusion of Electric Field

The electric field measured at the ground is indicative of the approach of charged clouds, as described in Section 2.2. Indications begin generally less than an hour before the first lightning strike reaches the ground. We therefore expect that the inclusion of electric field data will improve the network's predictions at time 'now' and '1/2 hour'.

(d) Conditioning Inputs

By conditioning inputs we mean inputs which are not necessarily indicative of lightning by themselves, but which influence the significance of the other data. Synoptic wind regime is one such parameter, since it has no spatial or temporal information, but is correlated with the probability of lightning. Stability indices, time of day, and season of the year also could be considered, the latter coming into play when nets are trained with data from multiple seasons.

(e) Use of Time Trends

Finally, the time trends in the data should be included in the ANS analysis. In connection with these trends, there are several means of preprocessing. For instance, the wind data at t_0 and the time derivatives of the earlier data might be used, or the prior data themselves might be presented as inputs along with data from t_0. Time variation might be especially valuable for processing electric field data, since the passage of thunderstorms often causes strong oscillations in electric field.

The following sections first review wind and wind divergence as predictors of lightning strikes, then discuss how the electric field at the ground varies with the approach of charged storm cells and finally summarize our understanding of the connection between lightning strikes and the prevailing synoptic weather regime.

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2. Lightning Prediction Parameters

Lightning prediction will integrate data associated with local storm cells and synoptic conditions. Local conditions include winds, cell motion, precipitation shafts, cell cloud top altitudes and dynamics. Synoptic conditions include weather regimes (generally vertical wind profiles and associated stability indices), season and time of day. This report discusses and combines selected weather elements into an ANS predictor which is built on that of Frankel et al. 1989b.

2.1. Networks Using Wind Fields

Two types of ANS lightning predictors using wind data will be considered. These are the current network using data from a single prior time to predict the future, and a network conditioned by a data product, namely divergence.

2.1.1. Current Network (1989)

The current KSC ANS predictor is an obvious place to begin considering alternative network layouts. Prediction of lightning strikes at KSC by Frankel et al. 1989b was made by a three - layer backpropagation network *such as is sketched in Figure 2-1*. The three layer architecture was chosen because it has been shown that any continuous mapping can be approximated by a three layer network Funahashi 1989. This network bases its predictions upon data from one time epoch (time t_0) at its input level.

This choice was made for simplicity in this pilot study. Often, time-series predictions are based on observations from more than one prior epoch. Lapedes and Farber 1987 investigate the properties of a generalized, nonlinear predictor based on a backpropagation ANS. Werbos 1990 shows another approach to constructing an ANS predictor based upon time series of data. This study commences this type of study with the simplest predictor input, namely that using a single time. What are the implications of a single time epoch ANS predictor? Clearly the magnitude of whatever feature the current network selects is used in making a prediction. The value of these magnitudes is considerable as Watson et al. 1987 and Frankel et al. 1989 have already shown.
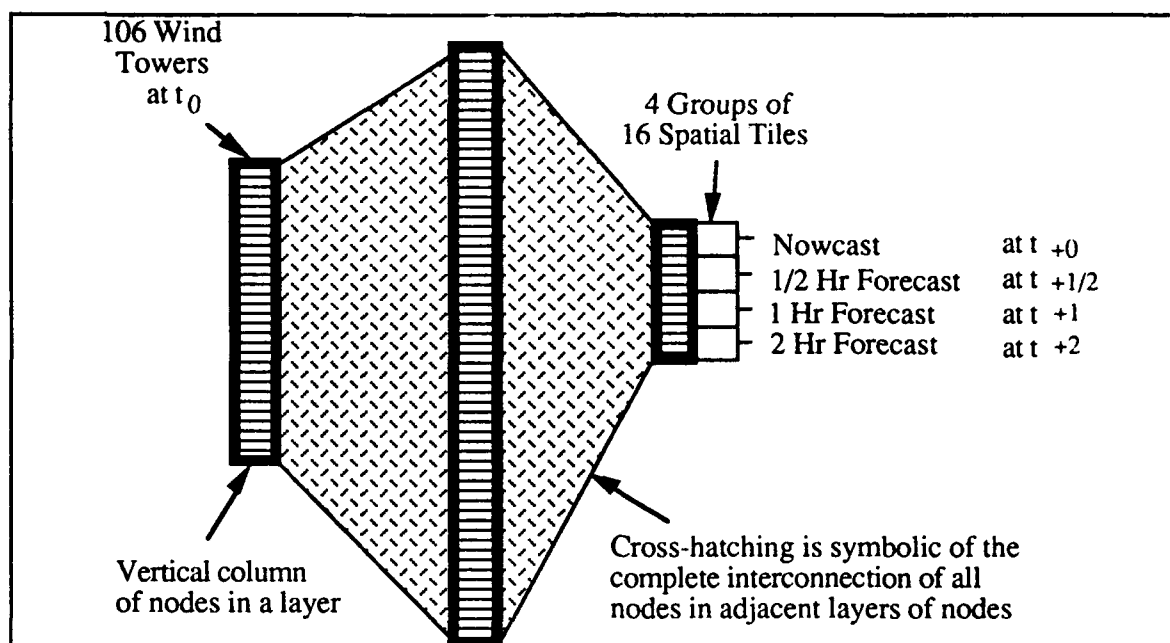
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Figure 2-1 106 x m x 64 backpropagation network of Frankel et al. 1989b used in forecasting KSC lightning strikes from wind data. Two wind speed component measurements at time t_0 are entered from the 53 wind sensors into the input row to the left to make $(t_0, ..., t_k)$ predictions.

The temporal evolution or history of measurements is ignored in this report. Time histories of weather measurements might be incorporated either as a temporal series of measurements or in a compressed form using temporal gradients of measurements. Addition of the time evolution information should further improve the predictions shown here at the expense of some complication in network operation.

2.1.2. Total Area Divergence

Watson et al. 1987 calculated the divergence of the vector wind field for sensors at one height above the ground at KSC. They then determined a threshold value of the divergence which indicated a high probability of a lightning event somewhere in the KSC area up to two hours afterwards. Lightning events usually occurred 80-120 minutes after the threshold was exceeded. The approach of Frankel et al. 1989b utilizes an ANS trained on raw wind fields and lightning strikes at KSC to predict lightning within specific spatial 'tiles' in KSC for specific time intervals.

Wind divergence emerged as the best current parameter in quantitative lightning forecasting, Lopez et al., 1986a and 1986b.

During cell formation rising thermals condense to cloud. This rise causes surface ('low level') winds to converge at the cloud base. Conceptually one can draw a ring at the cloud base around the periphery of which wind measurements are taken. By adding all the wind currents perpendicular to this periphery the amount of air 'converging' at the cell is measured. For uniform winds equal amounts of air are passing in one side of the circle and passing out the other leading to a zero divergence. During convective cloud formation, large negative divergences are observed.

A history of wind divergence is sketched in Figure 2-2 as divergence magnitude vs. time. As the cloud collapses, the flow reverses and a positive surface wind divergence appears. The lightning strike prediction method of Watson et al. 1987 'declares' a lightning strike 'very probable' when the wind divergence for all of KSC drops below -1.5 x 10^{-4} sec^{-1} as shown in Figure 2-2. This criterion was derived for the entire KSC area for a lightning strike in the 'near future' (i.e. hours). In addition to a fixed divergence threshold, the time evolution of divergence is significant.

Figure 2-2 Typical Thunderstorm Divergence History
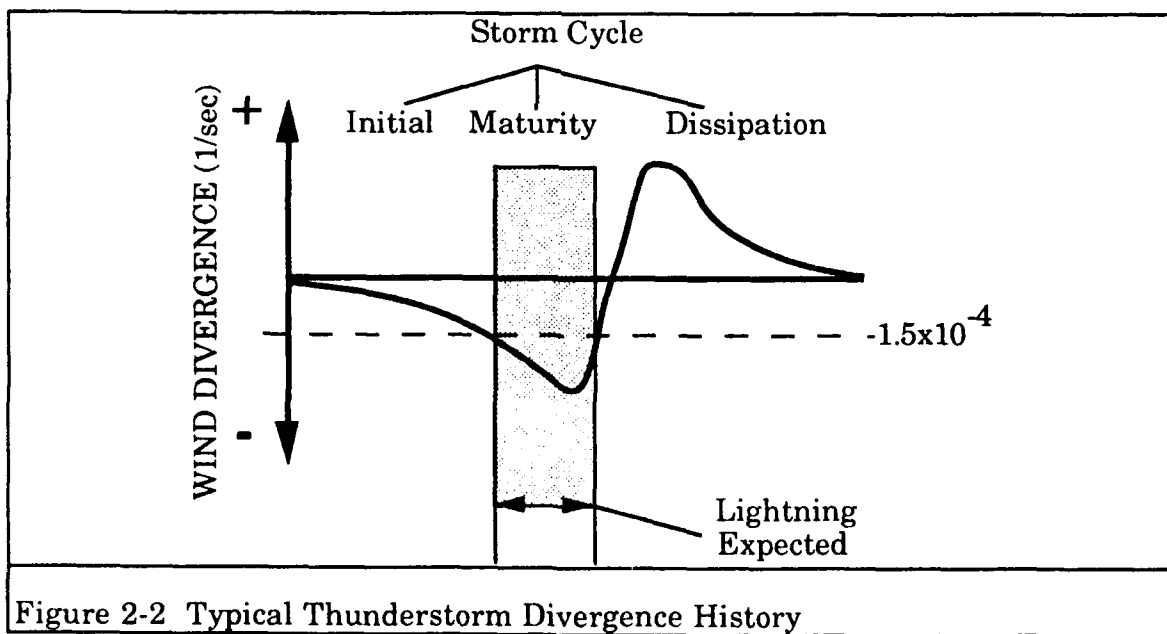
These results gave us confidence that raw wind data contained information from which an ANS system could learn to make lightning predictions. The neural network should learn the correlation of lightning with divergence, at least, and might build other significant correlations not present in divergence. Furthermore, the neural network's performance might even surpass

the Total Area Divergence predictor's if as input we used wind data from all heights above the ground.

Frankel et al. 1989b built a neural network for strike prediction using as predictor variables the wind field measured by all sensors at KSC. They subdivide the time for a predicted strike into four future time epochs (0-15, 15-30, 30-60 and 60-120 minutes), making the prediction based upon conditions 'now' (at t_0). Their ANS training uses as dependent variables the lightning strikes observed by the Lightning Location and Protection, Inc., (LLP) system in these same time intervals.

The prediction results of Frankel et al. 1989b were of the same quality as the results of Watson et al. 1987. Although the predictor of Frankel et al. 1989b also uses the wind fields at KSC, there are major differences in the inputs and in the way the two methods were evaluated, as summarized in Table 4-1. Yet there is enough similarity in these two methods for a direct comparison to be useful, see Frankel et al. 1989b.

Table 4-1 Comparison of Two Lightning Predictor Methods		
Aspect	**Frankel et al. 1989b**	**Watson et al. 1987**
Met Data	Raw wind data; All heights above the ground included.	Wind data product: divergence at one height above ground.
Data Grid	53 sites distributed irregularly horizontally and nonuniformly vertically	One divergence product for all of the KSC area at one height.
Time Grid	Uses data from only one prior time (t_0).	Uses reduced data from only one prior time (t_0).

Performance results from Frankel et al. 1989b show that wind fields give useful, though certainly not perfect, predictions of lightning strikes. Examination of the results suggests systematic errors may be present that might be addressed by including electric field data with wind data while using a longer time series (more history).

2.2. Electric Field

Lightning is an electrical phenomenon and measurements of local electric fields are directly related to the proximity of charged

clouds and the occurrence of strikes. The emphasis here is on short-term prediction so that the electrostatic effects of the approach of a charged cloud, as sketched in Figure 2-3, are of interest while the electrostatic effects during lightning strikes are not considered.
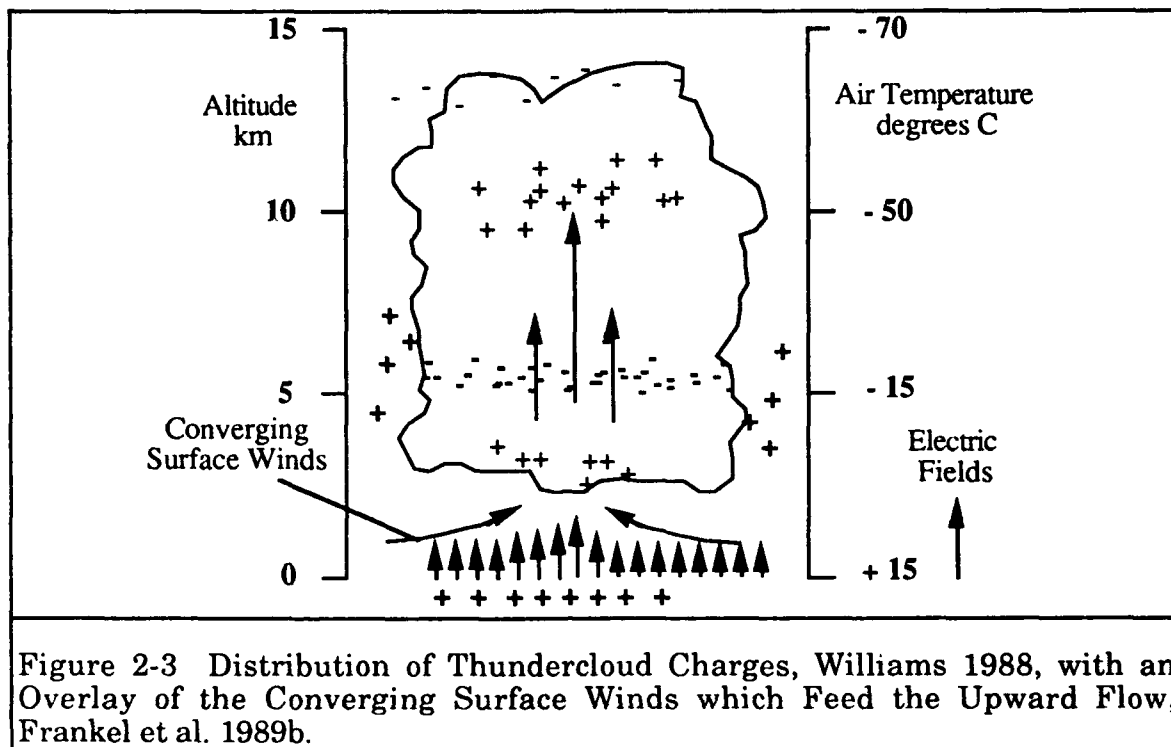

Figure 2-3   Distribution of Thundercloud Charges, Williams 1988, with an Overlay of the Converging Surface Winds which Feed the Upward Flow, Frankel et al. 1989b.

The storm cell contains charged regions, see Figure 2-3, which, as they move and change charge content, affect the vertical electric (called the electric field hereafter) field at the ground. Because of shielding by smaller, closer charged regions, the E field does not necessarily reflect the presence of the largest charged regions. The largest charged regions are the most likely to initiate strikes yet, because of charge shielding, the measured electric field is not necessarily directly related to incipient lightning strikes. This is particularly evident in photographs of lightning strikes which loop back on themselves. This type of behavior has led to the conclusion that the turbulent distribution of charges, not the three-dimensional electrical fields, largely determine lightning paths, Williams 1988. Local electric fields may respond to storms 20 to 30 km distant and sometimes 50 km away, Anon 1989b. The use of electric fields for predictions is therefore somewhat questionable, and is likely to be most useful for short-term predictions.
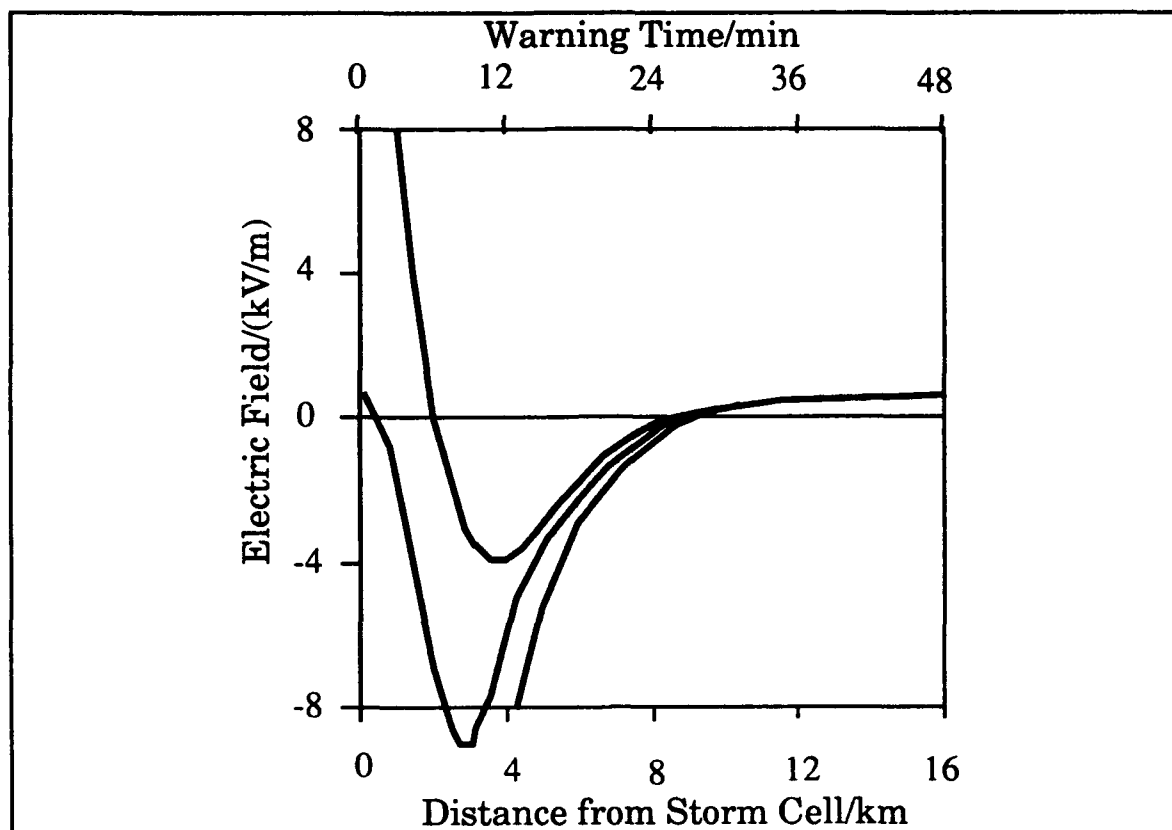
Figure 2-4 Variations in electric field intensity as storm cell approaches the measuring station, modified from Uman 1984. The storm is assumed to be approaching at 20 km/h.

Nevertheless, general behavior patterns in the electrostatic field, as measured by a field mill, are important for indicating the near-term approach of a cloud. Uman 1984 gives the electric field intensity at the ground resulting from three regions of charge as sketched in Figure 2-3. Let us take the upper positive charge to be 40 coulombs at 10 km altitude, the middle negatively charged layer to be -40 coulombs at 5 km altitude and the lower positive charge to be 0, 5 or 10 coulombs at 2 km altitude. All are assumed to be point charges. Note that this is a highly idealized distribution of charge; actual measurements sometimes show many layers of opposing charge, Schuur et al. 1990.

The effect of cloud distance, D, from the observing site is shown in Figure 2-4 which is taken from Uman 1984. Since the smallest charge is also the lowest charge, its greatest effect is at very short distances (or times). For short-term lightning prediction, from 15 to 30 minutes into the future, the roughly monotonic decrease in

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electric field intensity is an indication of the sizeable negative charge layer dominating the mid-cloud region.

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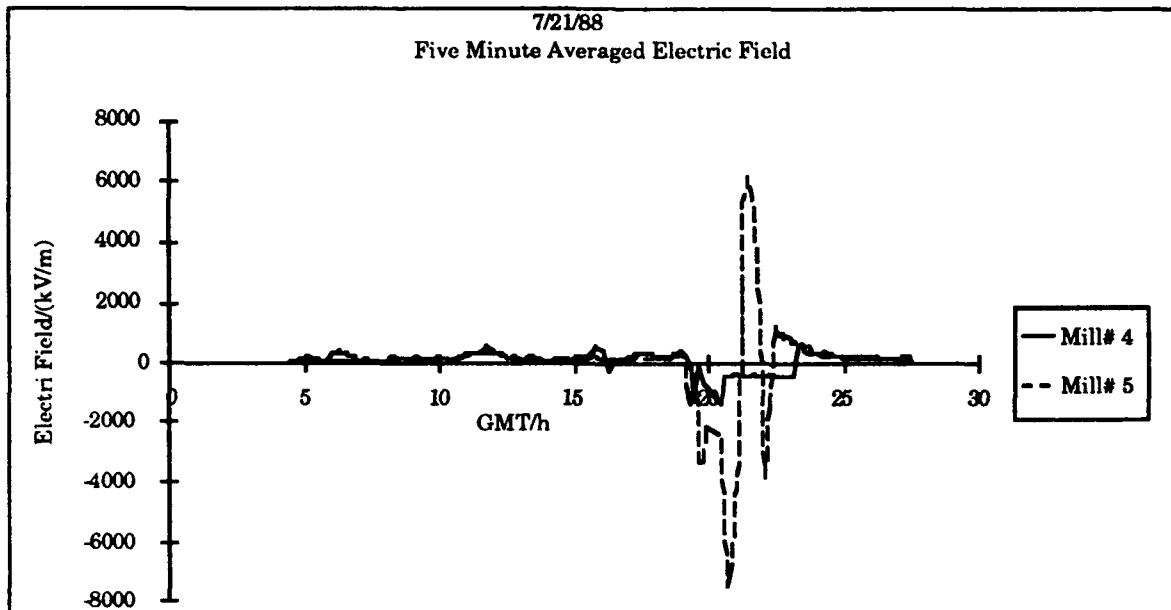**Five Minute Averaged Electric Field**

Figure 2-5 Measured electric field data for July 21, 1988. The time is expressed as UT from midnight local time on one day to midnight of the next. These data are courtesy of KSC.

'Field mills' are used to measure electric field intensity, Uman 1984, of which KSC data are used in this report, see Figure 2-5. The behavior above suggests the use of electric field measurements averaged over the same intervals used for the surface wind field. The electric field might be used as a 'conditioning' node for each ANS spatial 'tile'. This would require that there be an electric field mill in each tile, which is not the case. An alternative used here is to simply include all of the raw field mill data from the KSC area, averaged over a five minute time matching the wind data averages. Electric field intensities could be input as: magnitudes, spatial gradients, temporal gradients or combinations of these three. In this report, the magnitude of field intensity is used.

2.3. Synoptic Weather Influence

Several studies, conducted since 1983, have established qualitative correlations between synoptic weather conditions and subsequent lightning strike patterns in southern and central Florida. The earliest demonstration of this relationship is in Lopez, Holle & Balch 1983 which was followed by a look by Lopez & Holle 1987 at conditions in central Florida. The conclusion reached by the authors

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of this work was that the synoptic weather regime early in the day strongly influences subsequent lightning strike patterns.

2.3.1. Review of South Florida Synoptic Conditions

Lopez et al. 1983, showed that diurnal convective activity in south Florida is determined, to a large extent, by the type of synoptic flow pattern present during the day. It is reasonable to expect that these flow regimes are reflected in lightning activity. The flow regime is important since it determines the type of air mass (i.e., the atmospheric thermodynamic properties) in which the convective clouds are developing in response to the forcing produced by local sea and lake breeze circulations. Different flow patterns can bring dynamic influences in the form of enhanced forcing or suppression of convection. In south Florida during the summer, the principal synoptic flow regimes are determined by: (a) position of the Atlantic High in relation to the peninsula; (b) passage of tropical storms, and; (c) passage of mid-latitude perturbations.

Motivated by the need to have 'advance knowledge of the degree of lightning activity over a region in the next 12 to 24 hours' Lopez et al. 1984 took advantage of strike collections from the then recently deployed c-g lightning detectors together with digitized radar reflections and early morning atmospheric soundings. The lightning data were collected by two direction finders manufactured by Lightning Location and Protection, Inc. This study aimed at associating principal meteorological data (e.g., flow patterns) with lightning activity, rather than the exact timing and diurnal fluctuations of strikes. The principal meteorological data chosen are 'flow regimes' typical of south Florida.

In order to describe the overall flow in the region it is convenient to examine the entire wind direction profile. These are obtained in the morning from vertical soundings and are assumed to characterize the synoptic flow regime during the remainder of the day. These wind profiles are shown in Figure 2-6.

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Figure 2-6 Typical wind profiles for South Florida from Lopez et al. 1984.
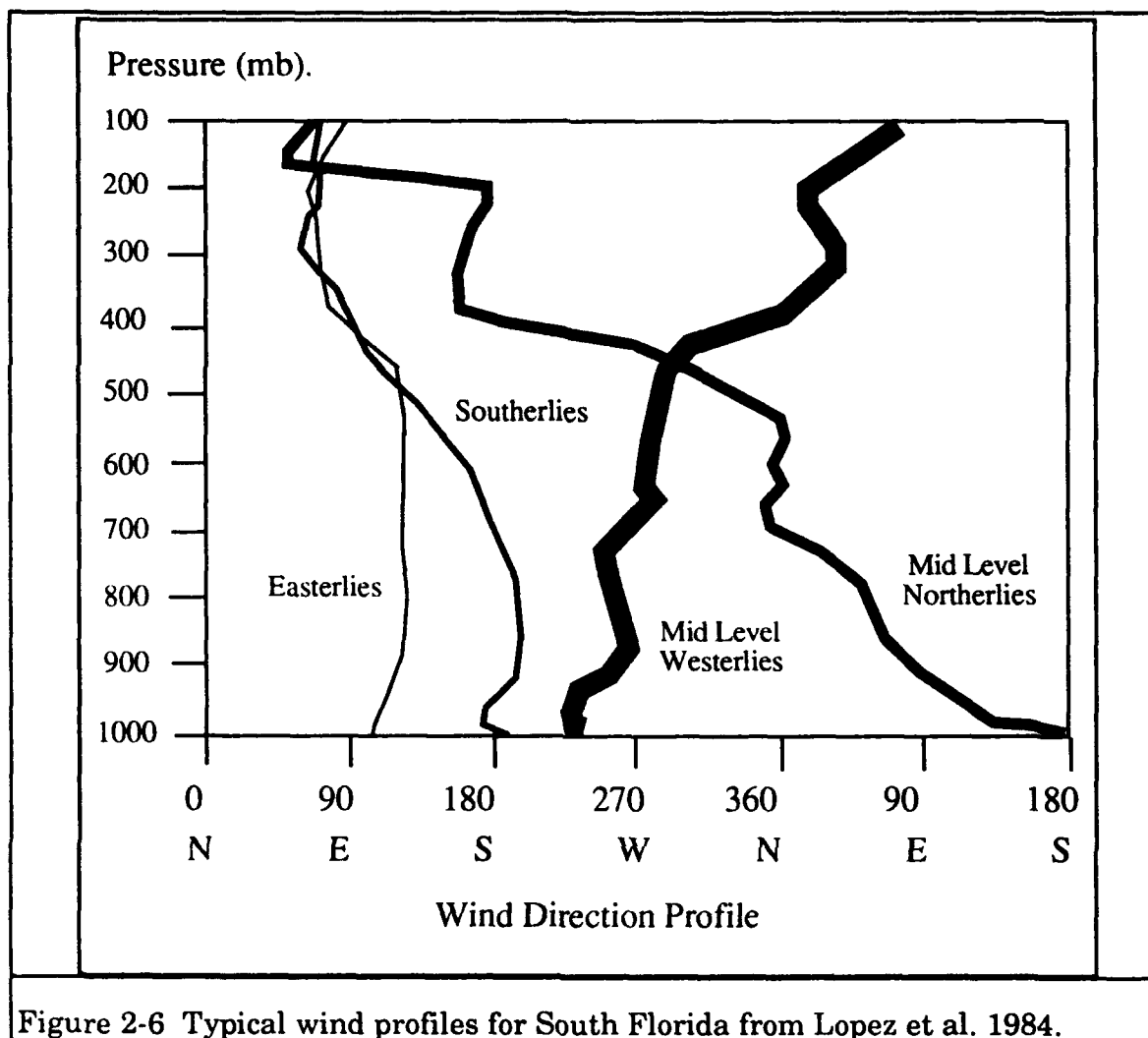
Wind direction profiles are given the following designations:

(1) Deep Easterlies: ESE winds predominate in a deep layer from the surface to 450 mb with very little wind directional shear. Above that level the winds gradually turn to the NE.

(2) Low Level Southerlies: SSW winds present in the layer from the surface to 650 mb. Beyond that level the winds turn SE and finally NE above 300 mb.

(3) Mid Level Westerlies: SSW winds very close to the surface changing to WSW/WNW in the 850-400 mb layer. Above that level the winds turn into a northerly direction, finally becoming NE as in all the other profiles.

(4) Mid Level Northerlies: NNE winds in a layer from 700 to 500 mb, with sheared layers above and below. In the lower part winds change from SW at the surface to NNE at 700 mb. In the upper layer the winds change from NNE to W, S and NE above 200 mb.

Lopez et al. 1984 show that knowledge of that morning's synoptic weather patterns gives indications of the activity patterns of the ensuing lightning strike activity. Specifically, when the soundings were averaged together by quartiles of lightning activity, within wind profile types, characteristic differences were found that gave a consistent picture of the factors determining different degrees of lightning activity. Lopez et al. 1984 conclude that relationships exist between daily flash activity and certain combinations of meteorological parameters detected early in the morning before significant convection develops.

This early study established that an important relationship exists between the general weather pattern and subsequent lightning strike patterns. Because of the possibility that 'south Florida' synoptic conditions may be different from KSC (mid-Florida) conditions, it is necessary to examine the case in central Florida.

2.3.2. Low-Level Wind Flow in Central Florida

Lopez & Holle 1987, investigated lightning cloud-to-ground strike patterns in the context of the prevailing wind direction. This approach was taken up based upon 25 years of study of the association between shower activity and low-level atmospheric activity.

In this study 24 hour diurnal lightning strikes (in the summers of 1983, 1984 and 1985) were classified by mean wind direction in the 1000 and 700 mb layer using the 'early morning' (0900 - 1100 EST) KSC sounding. Five classes defined four mutually exclusive 90° sectors:

(1) 'calm' (< 2 m/s);

(2) NE wind (23° to 113°);

(3) SE wind (113° to 203°);

(4) SW wind (203° to 293°), and;

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(5) NW wind (293° to 23°).

The NE and SW directions are perpendicular to the 'east' and 'west' coasts whilst the NW and SE directions are in the parallel sense. The mean wind direction profiles are shown in the Figure 2-7.
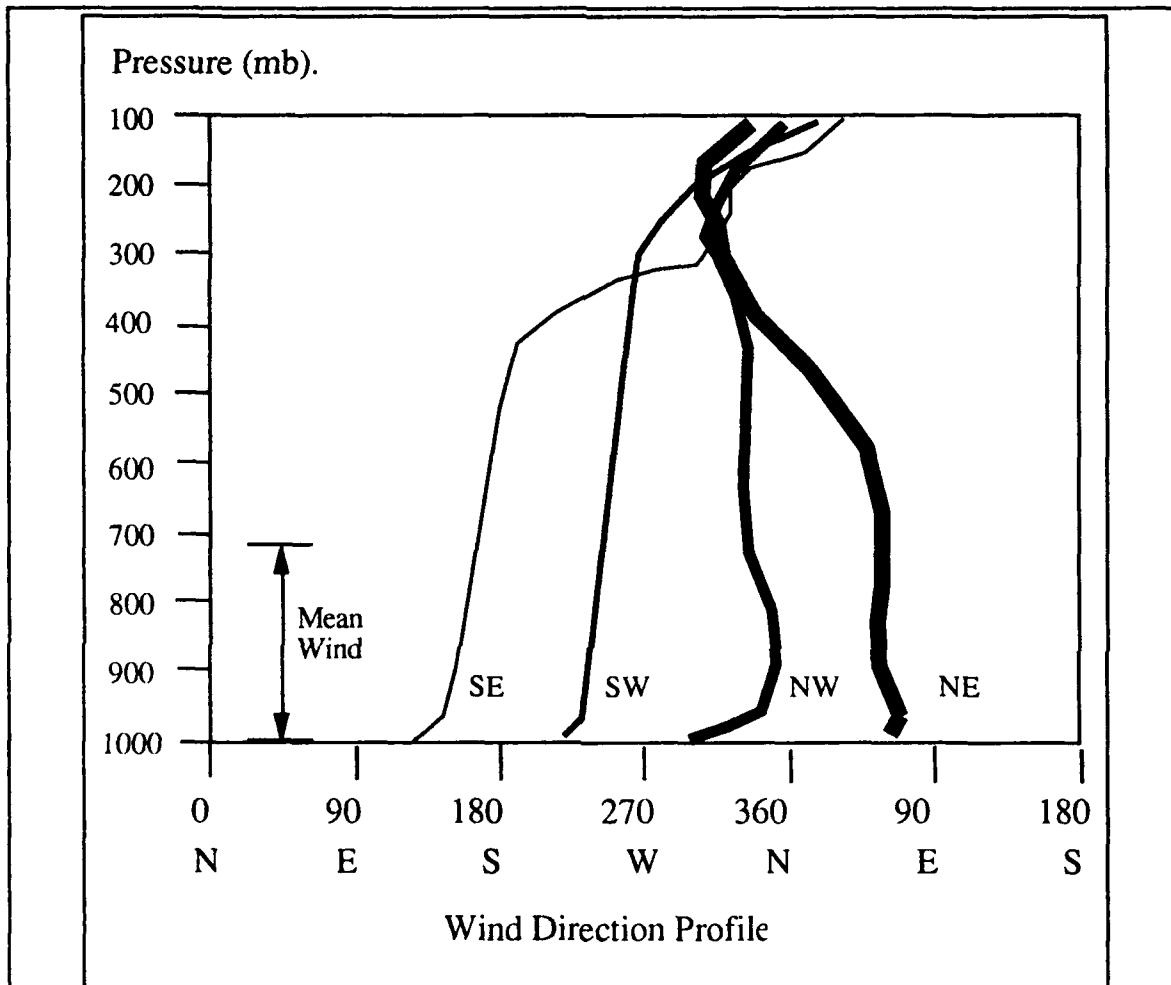
Figure 2-7 Mean wind direction profile for each wind direction group in the 1000 to 100 mb range. The wind direction between 1000 and 700 mb is used to identify the mean wind regime in Central Florida, Lopez and Holle 1987.

In general, NE days are least favorable for deep convection, being the most stable and driest. These days frequently reflect the presence of an anticyclonic center north of the region, bringing air that has had a history of subsidence over the region. SW days are moist and most unstable and so would be the most favorable for deep cumulus cloud development. These two groups differ the most from each other while the other groups show an intermediate potential in terms of combinations of moisture and instability. Maps over KSC of

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lightning flashes appear to be strongly influenced by the mean wind direction.

The observational evidence indicates that synoptic wind flow has a role in determining both the spatial and temporal flash distribution in central Florida. This influence seems to occur mostly through the interaction of the onshore/offshore low-level wind components of the prevailing (synoptic) wind with the regional sea breeze circulations. The prevailing flow has a role in determining the overall degree of flash activity through the advection of different types of air masses having stability and moisture contents that are favorable for, or detrimental to, deep convection. Lopez & Holle 1987 suggest that early morning low-level wind conditions can aid in forecasting the characteristics of lightning conditions during the day over central Florida.

3. Data Fusion & Time Series Prediction Networks

In this section we consider how additional data days, additional prior times, the divergence product, and an additional weather parameter, the electric field, might be included in the ANS inputs. Also considered is the implementation of time histories in weather forecasting.
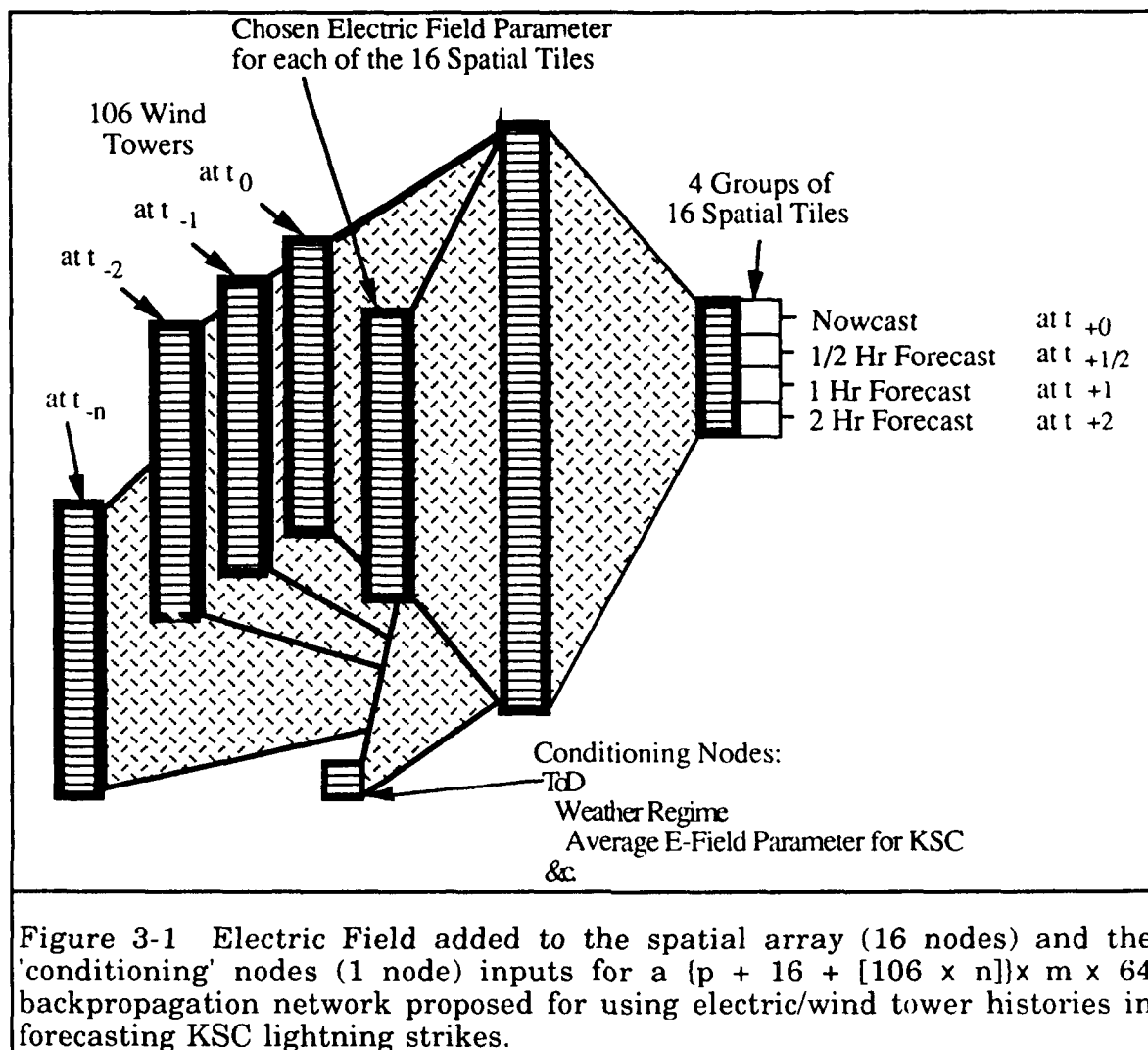
3.1. Networks for Winds & E-Fields

The combination of new wind data days with other types of data involves a form of 'ANS data fusion.' ANS for different kinds of input parameters have been developed and used successfully. For example, the plankton analysis networks of Frankel et al. 1989a combine flow cytometer optical data with sampling depth values to improve the classification of plankton species.

3.1.1. Strategies Considered

The fusion of winds and electric fields could be made at one (or more) of several levels. For the wind input, the full tower set, wind time series with p 'conditioning' nodes (see Figure 3-1) is assumed. For the electrical inputs, following the discussion of Section 2.2, 'Electric Field', a conceptually simple point to start modifying the ANS predictor for electric field phenomena is to add a set of conditioning nodes. Subsequently a separate array of electric field nodes could be used in much the same way that the wind sensor array is now input to the ANS, see Figure 2-1.

The electric field 'conditioning' node would simply be added to the other 'conditioning' nodes already pictured in Figure 3-1. In the lower part of that figure the "Electric Field" parameter would be added. How this parameter is derived is important. At first, it would be the <u>average electric field for all KSC</u>. Next the time and spatial derivatives for that average could be added. Hence, this electric field ANS looks just like that in Figure 3-1 using the chosen electric field parameter for all KSC.

When adding information about the spatial description of the KSC electric field, a new array of spatial inputs must be added as is pictured in Figure 3-1.

Figure 3-1   Electric Field added to the spatial array (16 nodes) and the 'conditioning' nodes (1 node) inputs for a {p + 16 + [106 x n]}x m x 64 backpropagation network proposed for using electric/wind tower histories in forecasting KSC lightning strikes.

There is now a range of ANS architectures to consider for winds plus electric field. Current resources are limited, so the architectures actually evaluated must be selected with care. As is often the case in scientific studies, consideration must be given to the trade-off between simplification and loss of information.

Here are two approaches. First, develop an electric field product which can be entered at a single node. Second, use the full set of electric field sensor data. That is the electric field/wind series elaboration of the ANS might eventually include the following sets of inputs being added to the Frankel et al. 1989b ANS:

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(A) 'Conditioning' Nodes Only (time of day, season, weather regime, etc.)

    (1) 1 average electric field for KSC,

    (2) 1 average electric field time/spatial gradient for KSC,

(B) Spatial Nodes with above 'Conditioning' Nodes

    (1) 16 average electric fields for each tile at t_0,

    (2) 16 average electric field gradients for each tile at t_0,

    (3) 16xn average electric fields for each tile at t_0 to t_n,

    (4) 16xn average electric field gradients 16 tiles at t_0 to t_n,

The electric fields and winds are measured (at KSC) at different rates. Winds are measured every 5 minutes while the electric field may be measured at rates up to 10 Hz. Therefore the user will have to reconcile different rates in building an efficient ANS predictor.
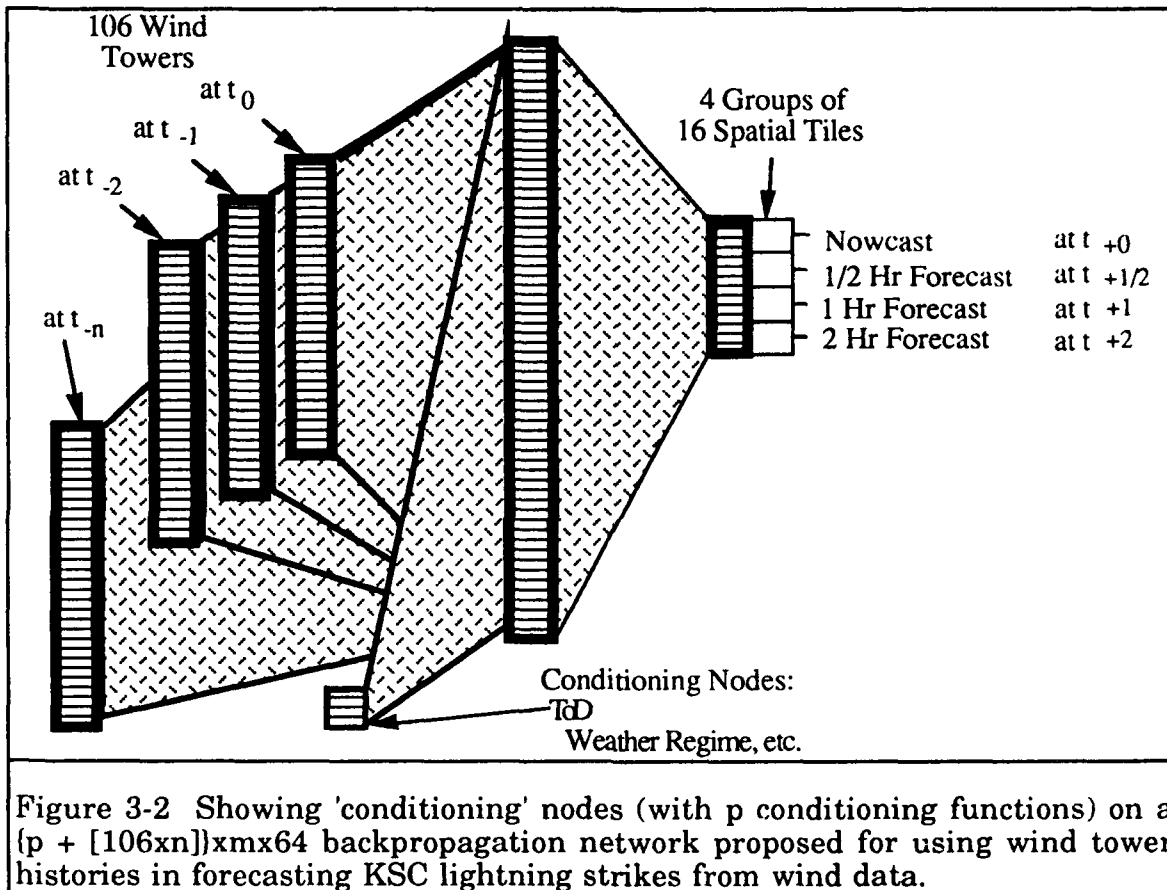
3.1.2. Strategy Adopted

The electric field data fusion strategy adopted in this study uses the data from each of the field mills as a separate input to the neural network. Since this will be the first attempt to employ the electric field data, it was preferable to retain all of the information at this early stage of predictor development, rather than to reduce it to a single conditioning input. Moreover, since there are only 31 electric field sensors, computing an input for each of 16 tiles does not offer a very great reduction in network complexity. The process begins with averaging the data for each field mill over 5 minute intervals to match the time intervals of the wind data. The averaging is done in a separate computer program which creates the input file for the network.

3.2. Synoptic Weather Networks

As in the 'depth' conditioned ANS of Frankel et al. 1989a, lightning predictions will be affected by overall influences such as the time of day and the weather regime. The 'Time of Day' (ToD) might be used with the additional days of wind data to be used beyond the single training day employed in Frankel et al. 1989b. This expanded

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training set should also be examined for the 'weather regime' characterizing each lightning day.

The weather regime (discussed in Section 2.3) can also be used to condition the network. The weather regime is the heading of the overall weather mass moving through the KSC area. This information could be derived from the sounding which is taken every day at KSC. Stability indices can also be derived from the soundings and used as conditioning inputs.

Figure 3-2 Showing 'conditioning' nodes (with p conditioning functions) on a (p + [106xn])xmx64 backpropagation network proposed for using wind tower histories in forecasting KSC lightning strikes from wind data.

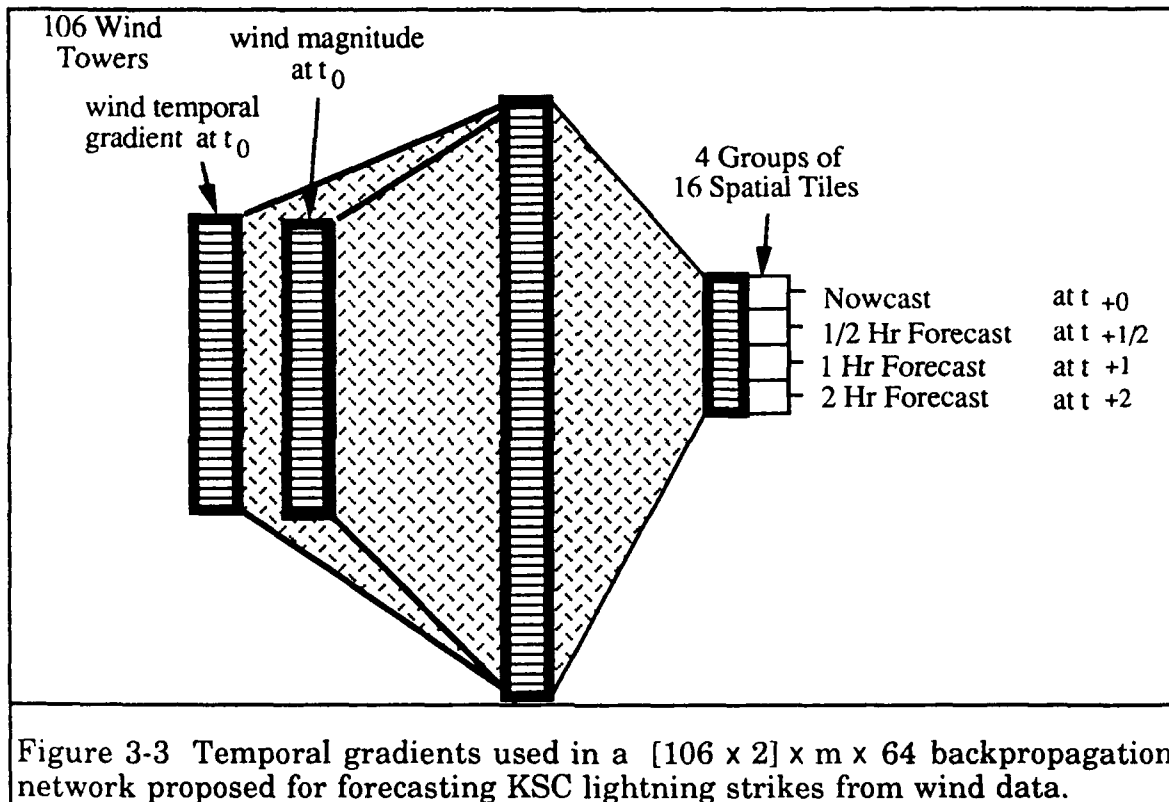The node layout for one or more of p conditioning inputs is sketched in Figure 3-2 as a direct input to the entire hidden node layer.

3.3. Time Series Prediction

Our discussion of thunderstorms indicates that surface wind fields undergo reasonably repeatable histories, Figure 3-2. One would expect to improve the predictive power of this class of network if more complete wind histories were included in the ANS input set.

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3.3.1. Multiple Time Series Network

A simple way to incorporate time histories is to add a series of input layers corresponding to the 53 wind sensors for a series of earlier epochs $(t_1, t_2, ..., t_n)$ than the single epoch now used (t_0). Adding other epochs in the wind tower series should be done in parallel. That is, data for all 53 wind sensors should be read simultaneously for the same prior time. This is the idea behind representing each prior time as a complete and equal vertical column in Figure 3-2. This appears to be a cumbersome approach.

Figure 3-3   Temporal gradients used in a [106 x 2] x m x 64 backpropagation network proposed for forecasting KSC lightning strikes from wind data.

One means of compressing the time history data required is to use the temporal gradient of the wind magnitudes as sketched in Figure 3-3. Other ANS time predictor approaches are those of Werbos 1990 and Patil and Sharda 1989. The latter predict, from standard time series, 1-12 months into the future using data from the previous 12 - 18 months.

4. Modified ANS Networks

All of the possible data processing, data fusion and time series prediction strategies described above are worth pursuing. Only a few of them could be investigated in the effort reported here. Those chosen for this study are listed in the following Subsection.
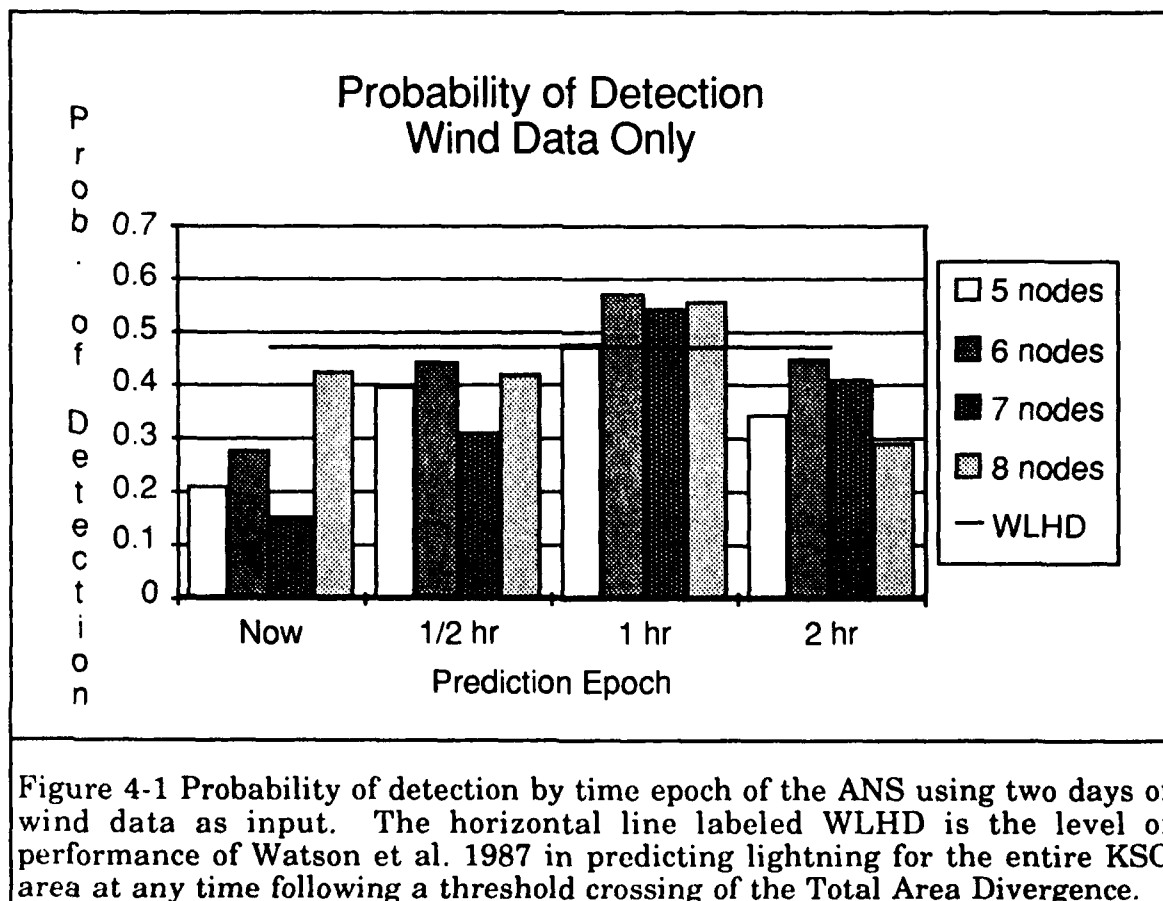
4.1. Chosen Prediction Parameters and Strategies

We sought to enhance the predictive performance of the ANS by several means:

(1) **Additional Lightning Days** - The use of additional days of wind data. Frankel et al. 1989b used one day (25 July 1988). Up to seven additional days are available for use;

(2) **Addition of a Data Product** - The Total Area Divergence has been shown to be of value for lightning prediction. Inclusion of this product will demonstrate the ANS system's ability to fuse disparate data and give a further assessment of the usefulness of divergence as a predictive parameter.

(3) **Addition of Electric Field Data** - Charged thunderstorm clouds, which are the source of lightning strikes, are detected by the changes in the Earth's electric field as they approach a meteorological station. Electric field data will be added to the wind data in an improved lightning predictor. It might be expected that using the time derivative of the electric field would improve its value for prediction, since the electric field undergoes large positive and negative oscillations during a storm, as shown in Section 3.2. Inclusion of the electric field data will receive less attention because of the difficulties of manipulating these data and their more doubtful value for prediction.

4.2. Modified ANS Predictor Performance

This report describes three extensions to our earlier work (Frankel et al., 1989b): (1) training the networks using more than one day of lightning data, (2) use of wind Total Area Divergence values as a 'context' for KSC, and (3) use of averaged electric field mill data.

Prediction performance is measured in terms of the probability of detection (PoD) and the probability of false alarm (PFA) as described in Frankel et al. 1989b. As before, a prediction is counted as correct only if lightning occurred in the predicted tile during the predicted epoch. PoD is the ratio of the number of spatial tiles and time epochs where the ANS system made a correct prediction of lightning occurrence to the number of tiles and time epochs where lightning occurred. PFA is the ratio of the number of tiles and time epochs where the ANS predictor falsely predicted lightning to the number of tiles and time epoches without lightning. These two quantities form the axes of the "Receiver Operating Characteristic" (ROC) graph, which is a standard means of evaluating predictive systems (Green and Swets, 1966). Improved ANS predictor performance was achieved, as measured by a higher PoD with a low PFA.

Figure 4-1 Probability of detection by time epoch of the ANS using two days of wind data as input. The horizontal line labeled WLHD is the level of performance of Watson et al. 1987 in predicting lightning for the entire KSC area at any time following a threshold crossing of the Total Area Divergence.

In this study, networks having one "hidden" layer were used exclusively. Networks with as many as 50 hidden nodes in this layer were investigated. In general, networks with more hidden layer

nodes achieve a lower total error at the end of training. However, the large networks did not perform as well on days of data outside their training set. This is to be expected; limiting the size of a network reduces its ability to learn every detail of its training data and in effect "forces" it to generalize.
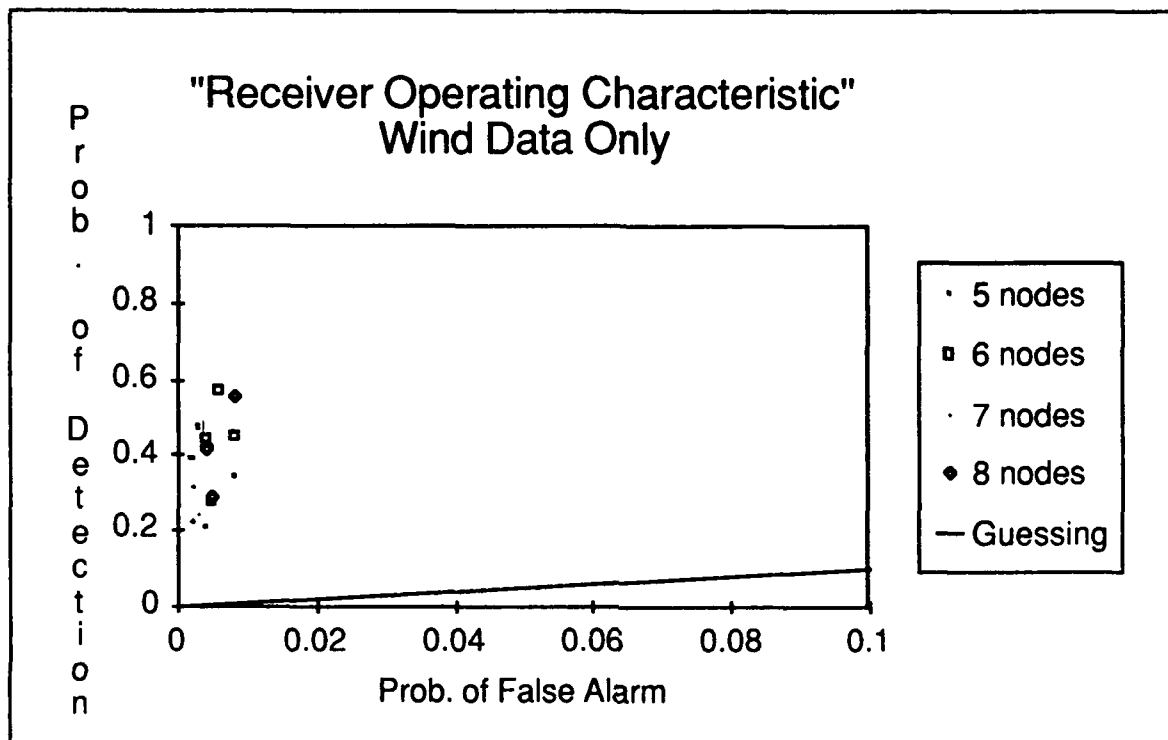

Figure 4-2 ROC graph of the ANS predictor using wind only as input. The diagonal line terminates beyond the right hand border of the figure, at the point where the probabilities of false alarm and detection are both unity. The performance of systems using a guessing strategy would fall somewhere on this line. Being in the upper left part of this graph, the points describing the ANS predictors demonstrate that they are performing substantially better than guessing.

Results are shown in Figure 4-1 for networks trained with wind data only and having 5, 6, 7, and 8 nodes in the hidden layer. The probability of detection is greater for the 5, 6, and 7 layer networks, with PoDs from 0.55 to 0.57. This maximum PoD occurs at 1 hour (30-60 minutes) in the future. The horizontal line in the figure marked WLHD shows the PoD obtained by Watson, et al., (1987) for predicting a lightning strike anywhere in the KSC area at any time after the Total Area Divergence crosses a threshold.

The PoD does not tell the whole story. A PoD of unity could be obtained by predicting lightning all of the time. On the other hand,

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the PFA for such a strategy would also be unity, whereas one would like it to be small. These considerations are displayed in the ROC curve in Figure 4-2. Often in such graphs, both axes extend from 0 to 1. In the ROC graphs of this report, the PFA axis has been expanded to show more detail. The diagonal line represents the performance of a system which is predicting by guessing with some probability. The line extends to the point (1, 1), which is beyond the edges of the expanded graph. The point (1, 1) represents a particular case of the guessing strategy: always predict lightning. The symbols represent the performance of the ANS predictor. Systems above the diagonal line in the ROC graph are doing better than guessing.
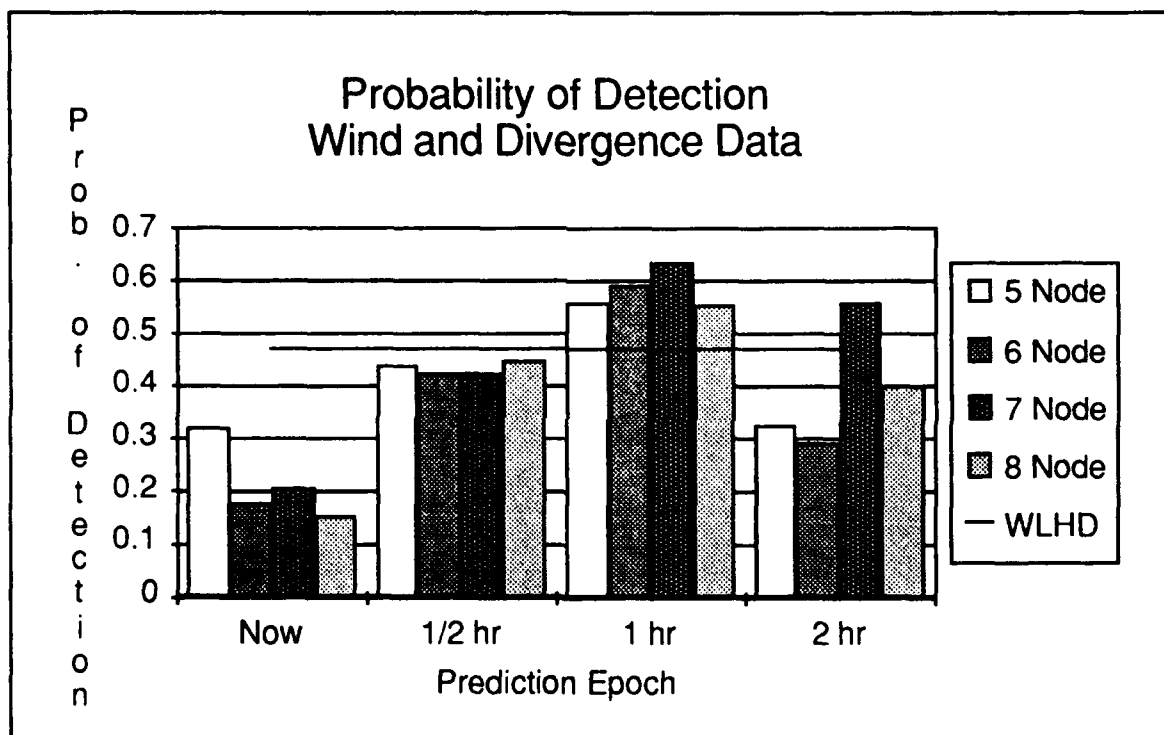

Figure 4-3 Probability of detection by time epoch of the ANS using two days of wind data and the Total Area Divergence as input. The horizontal line labeled WLHD is the level of performance of Watson et al. 1987 in predicting lightning for the entire KSC area at any time following a threshold crossing of the Total Area Divergence.

Predictor performance is improved at 1 hour by including the Total Area Divergence product as an input to the network. This is shown by comparing Figures 4-1 and 4-3. In this case, the 7 hidden node network performs best, with a PoD of 0.63. Performance also improved noticeably for the 7 and 8 node networks at 2 hours, and for all but the 6 node network at 1/2 hour.

"Receiver Operating Characteristic"
Wind and Divergence Data

Probability of Detection

Probability of False Alarm
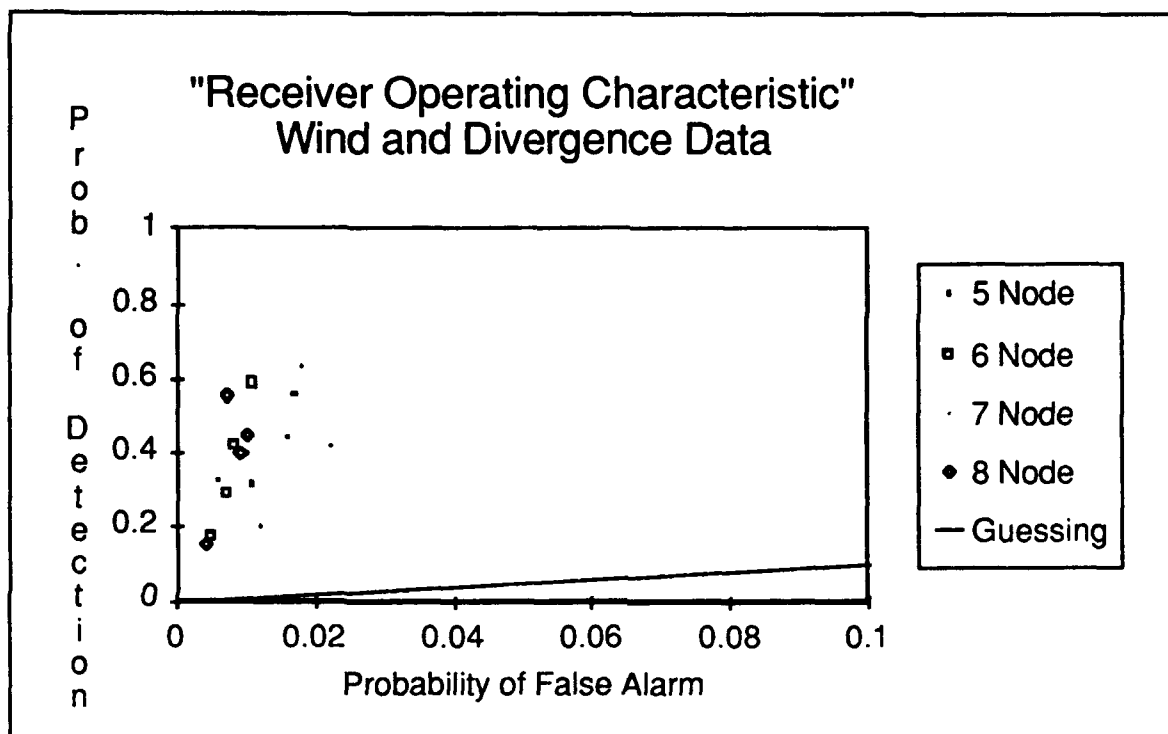
- 5 Node
- 6 Node
- 7 Node
- 8 Node
— Guessing

Figure 4-4 ROC graph of the ANS predictor using wind and Total Area Divergence as input. The diagonal line terminates beyond the right hand border of the figure, at the point where the probabilities of false alarm and detection are both unity. The performance of systems using a guessing strategy would fall somewhere on this line. Being in the upper left part of this graph, the points describing the ANS predictors demonstrate that they are performing substantially better than guessing.

The ROC graph for the predictors using wind and divergence is shown in Figure 4-4. As in the case of the wind networks described in Figure 4-2, predictor performance is substantially better than guessing.

Figure 4-5 shows the probability of detection for networks using wind, divergence and electric field as input. Network performance is comparable to those of the other networks. There is, however, one area of real improvement. As discussed in Section 5, the value of the electric field data was expected to be an improvement of prediction performance in the early time epochs. In fact, one network performs significantly better in near term prediction than networks without electric field input, namely the ten node network. This result is shown more clearly in Figure 4-6, where for each training data suite, we plot the prediction performance of the network which performs best in the most time epochs. While these results using electric field

are preliminary, they do suggest that electric field data can significantly improve near term prediction performance.
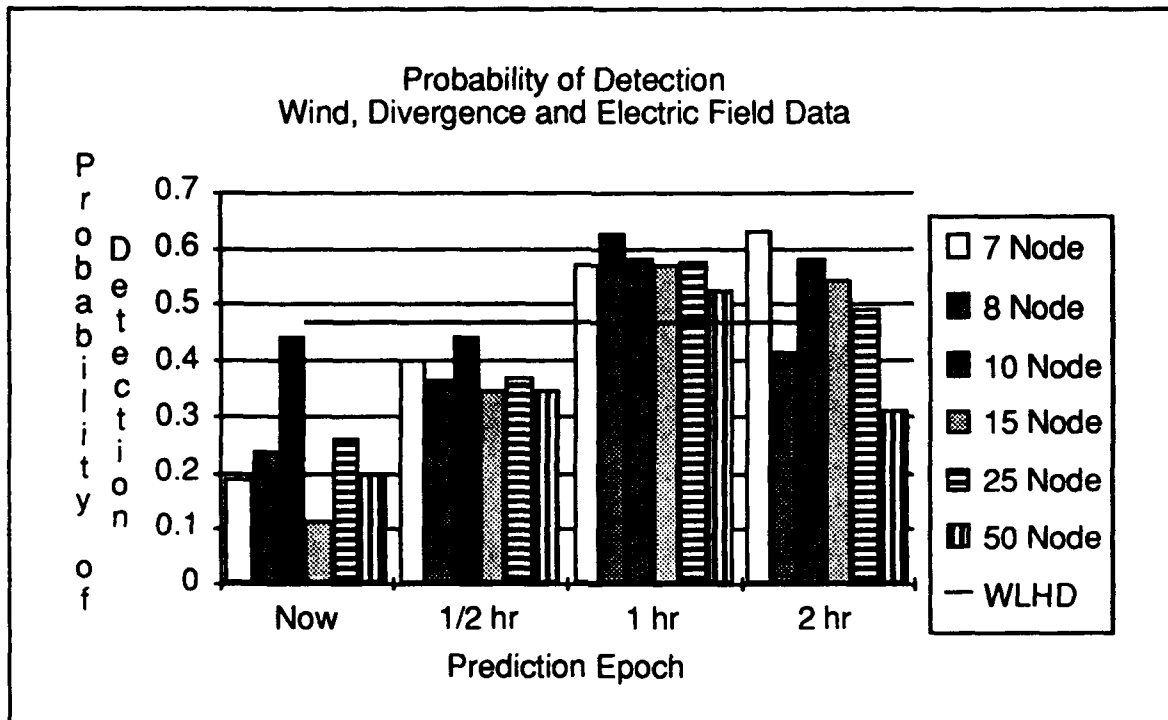

Figure 4-5 Probability of detection of the ANS using two days of wind data, the Total Area Divergence, and the electric field data as input. The horizontal line labeled WLHD is the level of performance of Watson et al. 1987.

Prediction results achieved are, for the test days, superior to the PoDs of the previous state-of-the-art reported by both Watson et al. 1987 and Frankel et al. 1989b. The improving trend in lightning prediction over the last few years is shown in Figure 4-7. These advances begin with the demonstration of Watson et al. 1987 (WLHD) of the prediction of subsequent lightning strikes for the entire KSC area at any time after a Total Area Divergence threshold crossing. Next Frankel et al. 1989 applied ANS learning and subdivided the predictions into detailed 'time epochs' and 'spatial tiles.'
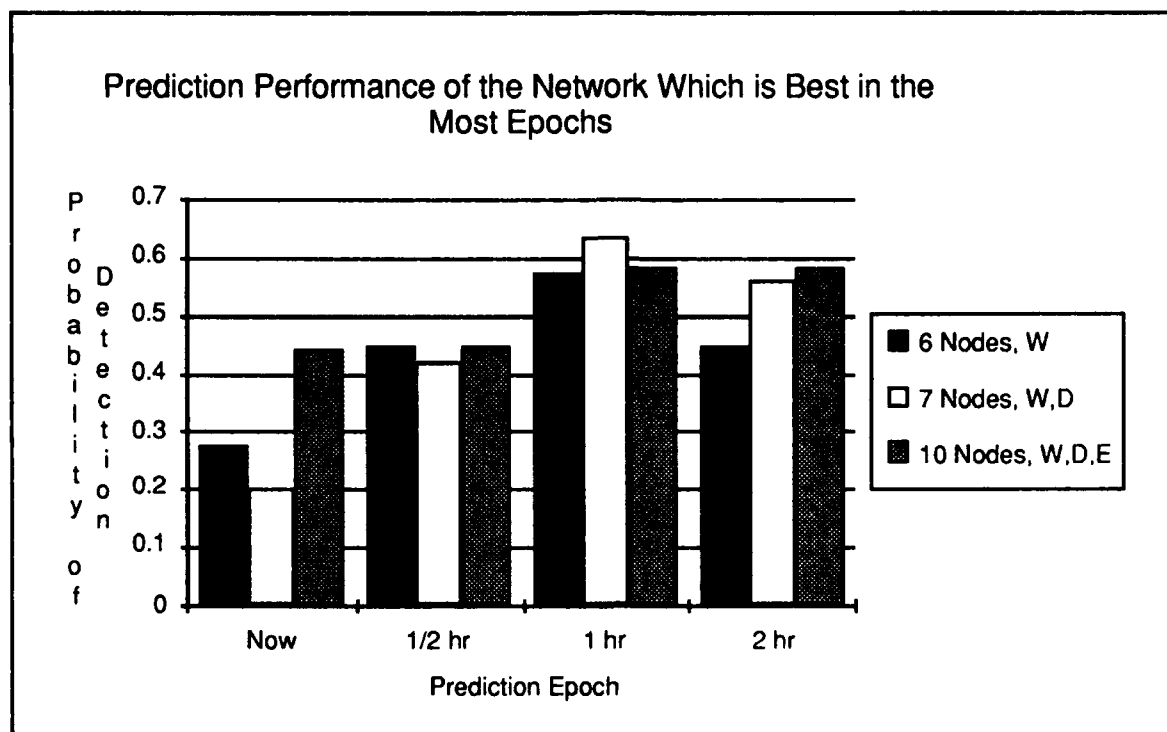
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Figure 4-6. Prediction performance for a selected network for each of the training data suites. "W", "W,D", and "W,D,E" designate training data suites of wind field, wind field and divergence and wind field, divergence, and electric field, respectively. Prediction improvements are evident at 1 and 2 hours due to divergence and at time Now due to electric field.

This work shows further improvement by use of more training days, the combination of wind and convergence data and the addition of electric field data. Even the modest extension of training sets to 2 days from 1 day shows marked improvement at 1 Hour.

Note that the criteria used by Watson et al. 1987 to declare a correct prediction are much less stringent in both spatial and temporal precision than those used in this study and our previous study. Using neural networks and including more data and data products as input has improved lightning prediction performance substantially.

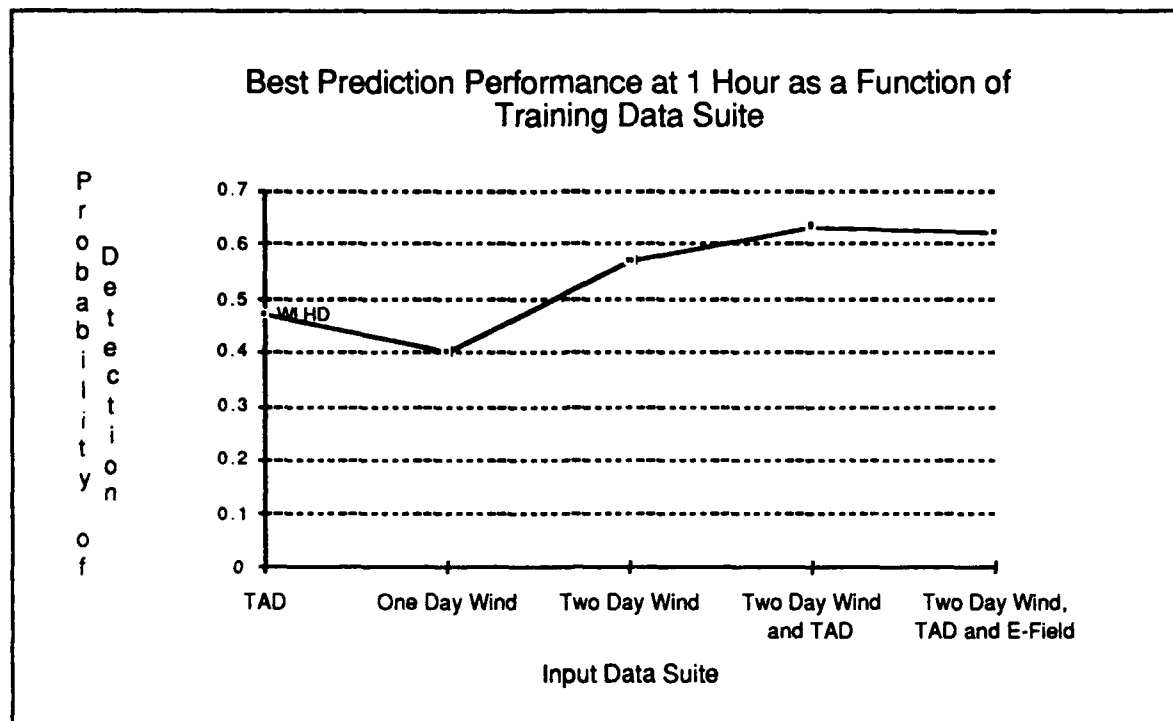**Best Prediction Performance at 1 Hour as a Function of Training Data Suite**

Figure 4-7 Trend of lightning prediction performance as a function of the data used for training and prediction. "TAD" indicates the Total Area Divergence product. The point labeled "WLHD" is the study of Watson et al. 1987, using the TAD threshold crossing technique. Other points are from Frankel et al. 1989b and the present study.

Upon comparing both Figures 4-6 and 4-7 the ANS predictor has performed well predicting lightning strikes for defined times in the future, has systematically improved with additional wind data, has improved as new types of data (convergence and field mill values) are used, and indicates the epochs in which one type of data is particularly useful (field mill data at short future times).

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5. Recommendations

A thunderstorm's progress over KSC affects loca weather parameters: precipitation, cloud cover, winds and electric fields. Watson et al. 1987 developed correlations between the present surface wind divergence and lightning strikes over the next few hours. Using ANS to process surface winds, Frankel et al. 1989b built the first automatically trainable lightning predictor. Its performance was comparable to that reported by Watson et al. for wind divergence.

Several approaches are considered in this report for improving the ANS lightning predictor. Those that were tried were largely successful. Further improvement can be expected by developments in the following areas:

(1) **Additional Lightning Days** for more representative training

> The larger PoD values shown in Figure 7-7 are believed to result from the use of larger, more representative data sets for training the networks. In our earlier study, one day of data was used for training. In this study, the number of days of data was increased to two. Better performance and more generalization is expected if weeks, months and even years of data are used for training.

(2) **'Conditioning' Input Nodes** for synoptic weather conditions

> 'Context' input nodes can be used for introducing the synoptic weather discussed by Lopez et al. 1987 in connection with lightning activity over central Florida.

(3) **Additional Lightning Past Times** for time evolution

> Frankel et al. 1989b used wind data at a single time, t_0, in the ANS predictor to forecast strikes at t_0, $t_{+1/2}$, t_{+1} and t_{+2}. Lapedes & Farber 1987 showed the value of an ANS for generalized, non-linear predictions and for providing a 'mapping' of the underlying systematic behavior of a system. The use of a greater time series (e.g. t_0, $t_{-1/2}$, t_{-1}, t_{-2}, &c.) of wind data should be considered.

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Another approach to using neural networks has recently been described by Werbos (1990). This paper describes "backpropagation through time" for describing learning the behavior of dynamical systems. It would be interesting to investigate the performance of that network architecture for lightning prediction.

(4) **Addition of E-Fields** adds an independent predictive variable

Lightning strikes at distances of 50 km induce changes in the Earth's electric field, Anon 1989b. Electric field data were combined with wind data in the ANS lightning predictor in the hope of obtaining improved performance, particularly for nowcasting. These results are preliminary; further investigation is warranted. Besides more extensive training, preprocessing of the electric field data might be very useful. For example, the time derivative of the electric field might have better predictive power than the field magnitude, or both together might be best.

(5) **Exploration of Prediction Thresholds for Risk-Benefit Analysis**

The ROC region used in this study is restricted to the lower left hand side of the ROC curve shown schematically in Figure 5-1. Other operating points on the ROC curve can be obtained by changing the ANS system's prediction threshold. The optimum point of system operation should be chosen by a risk-benefit analysis of lightning prediction. The small extent of the ROC explored shows the need to vary the ANS system's threshold so that the ROC may be better specified in future work.

(6) **Proper comparison to prior predictors.**

Another interesting task would be the summation of the ANS predictor detailed results (by epochs and tiles) to make a direct comparison with the results of Holle et al. 1987. Moreover, a detailed analysis of the ANS prediction performance (by epochs and tiles) would provide important information on the predictor performance.

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This would be especially illuminating for the value of ANS predictors designed with and without other measurements (e.g. electric fields).
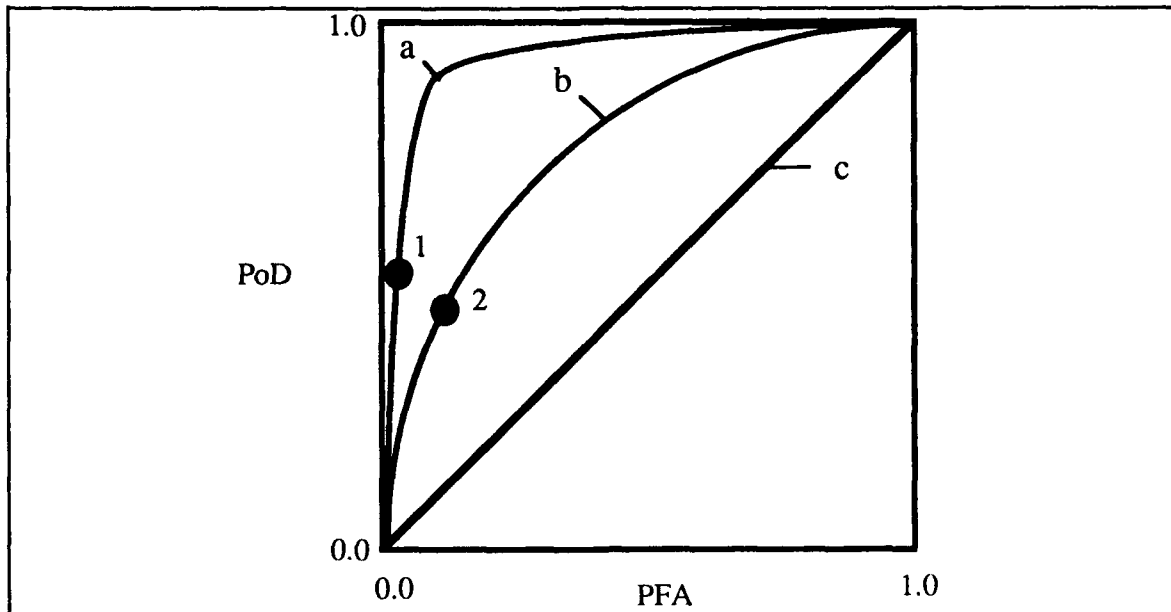

Figure 5-1 Schematic ROC graph. Performance evaluations in this work lie in the lower left-hand quadrant. The spread now observed in Figures 7-2 and 7-4 does not allow extrapolation of the ROC curve, which may resemble either a or b.

In this report three approaches were carried out: (1) use of additional lightning day data, (2) use of averaged wind divergence values as a 'context' for KSC, and (3) use of time-averaged electric field mill data for KSC. Improved ANS predictor performance, measured by both higher PoD and low FAR, was attained.

The value of using additional training days has two implications for ANS operational predictors. Further improvements can be expected from large data sets covering two or three seasons of KSC data. Second, once in operation (on site) a predictor's performance will improve, by incremental learning, during the course of routine, continuous data collection. This will help military meteorologists who often have limited acquaintance with local weather conditions due to their rotating tours of duty, Pickle 1990.

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